DESIGN OF MYOELECTRIC CONTROL SYSTEM USING MACHINE LEARNING TECHNIQUES

SYNOPSIS OF THE THESIS

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1. Introduction

Machines or computing systems are built to make lives convenient and easy for human beings. The ease of use of machines for human beings depends on the interface the machine provides for human beings to interact with it, to view output or to give some instructions to the machine. Human beings communicate effectively via speech, gestures, writing, typing etc. Human beings can make use of the same methods to communicate with a machine. To communicate via speech or gestures would not require a user to learn new languages as long as the user can perform some gestures or can speak. The availability of low-cost commercial off-the-shelf sensors and computer vision systems and rapid improvements in miniaturized and efficient electronic systems has opened up interesting application scenarios of Gesture Based user interfaces such as Spatial Hand Gesture recognition system and Myoelectric Arm Bands. Computing systems commonly have interfaces such as a Command Line Interface (CLI) or a Graphical User Interface (GUI). They require the use of I/O Devices such as Mouse, Keyboard to give instructions. The interface should facilitate efficient and comfortable interaction between the Human user and the machine.

Artificial intelligence can be used to model the user interaction to have a personalized, efficient interface between the user and the machine. To make this possible a variety of sensors are available in the market. For communicating with speech, a microphone is the I/O hardware required. For communicating with gestures, spatial hand gesture recognition systems can be used or myoelectric sensor can be used. For spatial hand gesture recognition, camera or devices such as leap motion controller can be used. Myoelectric Sensors can be used to tap into myoelectric signal produced during the muscular contractions when performing gestures with the hand. Artificial Intelligence techniques can be used to identify unique patterns in the myoelectric signal generated for distinct hand gestures. Artificial Intelligence involve methodologies such as machine learning, deep learning, reinforcement learning and generative learning. Methodologies such as deep learning algorithms may be computationally intensive and may require very high-performance Graphical Processing Units (GPU) and High-Performance Central Processing Units (CPU) along with large Random-Access Memory (RAM) storage. The developments in the electronics industry have made it possible to have commercially viable high-performance computers with High performance CPUs and GPUs available off-the-shelf in stores. This makes it possible for high performance computing to be available to a wider user base. This has led to rapid developments in the domain of Artificial

Intelligence. A wide variety of wearable technology is available in the market due to the developments in the electronics industry. The wearable devices can be used for monitoring health of a person as well as for control applications. The persons bio-signals can be tapped into in a invasive manner and using learning algorithms analytics can be derived from the data for health diagnosis such as Electrocardiogram (ECG), Electromyogram (EMG) or Electroencephalogram (EEG) or for control applications such as myoelectric systems or Brain Computer Interfaces (BCI).

A combination of Learning Algorithms and Wearable Devices can be used for implementing sophisticated Human Machine Interfaces for Health care applications and for Controlling Machinery. Exoskeletons are wearable robots that are rigid structures that operate alongside human limbs. Prosthetic arms and limbs are machines that assist people with limb amputations in Activities of Daily Living (ADL). Exoskeletons and Prosthetics can be controlled effectively by human machine interfaces. Powered Exoskeleton and Prosthetics enable the rehabilitation of people with limb impairment and amputations. Powered exoskeletons can also be used to enhance the ability of a human being to assist in lifting heavy objects and also to move larger distances with reduced effort.

The HMI in these exoskeletons and prosthetics require recognition of gestures. Among the gestures used by HMI, hand gestures are the most natural and preferred way of control and interaction. Computer vision-based gesture recognition are prone to some problems such as, finger occlusion which can be very high depending on point of view, because of which, multiple gestures can look similar to a passive camera, the required video acquisition infrastructure, the requirement for a clear line of sight and constant lighting, resolution and range problems, and frame rate.

Sensors are the interface that bridge the gap between the physical world and the embedded system. Sensors are the first elements in the architecture of a HMI system. The use of sensors interfaced with the muscle of the arm represents the most physiological approach considering that the muscle tissue is the final actuator in the control of hand movements. The signal acquired by the muscle activity is the Electromyogram (EMG) Signal which is widely used in clinical applications. The challenge lies in the acquisition and processing of EMG Signals with resource constrained systems unlike the table top setup used in clinical applications. Surface

EMG Signal represents the electric voltage due to the depolarization of the outer muscle fibre membrane [1].

Machine learning is a term that was coined in 1959 by Arthur Samuel, a pioneer in the field of Computer Gaming and Artificial Intelligence (AI). It has become a buzzword in the recent years and research in this field has gained a lot of momentum due to the significant improvements in high performance computing systems from those that could process only a handful of bits to those that can handle gigabytes or terabytes of data. The advancement in these exoskeleton and prosthetic technologies has propelled forward the study of machine learning oriented EMG signal pattern recognition. Machine learning is the use of computational tools to extract and understand a pattern within data. The recognition of these patterns is then directed towards an end application, such as recognizing a human action, and through it, the user's intent. At the heart of the gesture-controlled machinery, is a computing system that is used as a myoelectric control system to identify the different intended gestures of the user. The myoelectric control system makes use of machine learning techniques to perform classification of different gestures.

The classic machine learning technique involve classification methods such as Decision Tree Classification Algorithm, Random Forest Classification Algorithm, Naïve Bayes Classification Algorithm, Support Vector Machine Classification Algorithm, Logistic Regression Classification Algorithm, K-Nearest Neighbour Classification Algorithm and Artificial Neural Networks Classification Algorithm and Dimensionality Reduction Methods such as Principal Component Analysis and Linear Discriminant Analysis. The deep learning algorithm used in the study is a 1-D Convolution Neural Network.

Any intention, such as that to perform a gesture with the hand, originates in the brain. This information then travels through the Central Nervous system via the spinal cord and then the signal travels through the appropriate peripheral efferent nerve and end up causing contractions in the muscle fibres leading to the gesture being actuated in our hands. This is true for any voluntary motion performed. The information travels from the brain to the muscle fibres in the form of electric signals. This signal or action potential is transmitted through the neuron. The human body is composed of living tissues which generate electrical signals. Bioelectric potentials are generated at cellular level.

EMG Signals can be used to generate device control commands for machinery such as prosthesis and in generic human-machine interface. Information of each gesture can be obtained from EMG signal. However, as the signal is stochastic, amplitude cannot give useful information. Amplitude would indicate the presence or absence of a gesture. To get more insight into the gesture, such as the type of gesture performed, features must be extracted from the EMG signal. Each gesture can then be represented by a feature vector. The feature vector would be unique for each gesture and similar class of gestures would have similar feature vectors, but not exactly the same. Myoelectric Control Systems are the systems which are powered by machine learning or deep learning algorithms, which can take as input the EMG signal from the muscles and interpret the EMG Data and taker appropriate control actions. Such myoelectric control systems can be used to control Prosthetic limbs or Exoskeleton suits or even regular computing applications.

2. Literature Survey

In [2] the authors have assessed the feasibility of using support vector machines in analysing myoelectric signals acquired using an off the shelf device, the Myo-Armband from Thalmic Lab, when performing hand grasp gestures. Twenty-six participants took part in the study wearing the armband and producing a series of required gestures. Support vector machines were used to train a model using participant training values, and to classify gestures produced by the same participants. Different kernel functions and electrode combinations were studied. They have also contrasted different lengths of training values versus different lengths for the classification samples. The overall accuracy was 94.9% with data from 8 electrodes, and 72% where only four of the electrodes were used. The linear kernel outperformed the polynomial, and radial basis function. Exploring the number of training samples versus the achieved classification accuracy, results identified acceptable accuracies (> 90%) for training around 2.5s and recognizing grasp with 0.2s of acquired data. The best recognised grasp was the hand closed (97.6%), followed by cylindrical grasp (96.8%), the lateral grasp (93.2%) and tripod (92%).

In [3] the authors have discussed evaluation of the Myo-Armband for the classification of hand gestures. Pattern recognition-based control systems have been widely investigated in prostheses and virtual reality environments to improve the quality of life of an amputee. Most of these systems use surface electromyography (SEMG) to detect user movement intentions.

The Myo-Armband is a wireless wearable device, developed by Thalmic Labs, which enables EMG recordings with a limited bandwidth (<100Hz). The aim of this study was to compare the narrow bandwidth of the Myo-Armband with the full EMG spectrum captured by a conventional EMG acquisition system to assess its suitability for pattern recognition control. A crossover study was carried out with eight able-bodied participants, performing nine hand gestures. Six features were extracted from the data and classified by Linear Discriminant Analysis (LDA). Results showed a mean classification error of 5.82 ± 3.63% for conventional system and 9.86 ± 8.05% for Myo-Band with no significant difference (P = 0.056). This implies that Myo-Band may be suitable for pattern recognition applications despite the limitation in the bandwidth, based on LDA Classification. Suggested future work by the authors is to evaluate the Myo-Band's performance with other classifiers and its behaviour in real time compared to conventional systems, to fully determine its potential in pattern recognition, and more specifically, prosthesis and rehabilitation.

The research work involving Thalmic Labs, Myo-Arm Band is still in its infancy. The authors have explored the usage of LDA Classification and have suggested it to be suitable for pattern recognition. In [4] the authors have tested the performance of Myo-Armband & concluded that it is a device with high potential as the results showed that the percentage of signal distortion and signal to noise ratio of the signal obtained by Myo-Armband was lower than those of a conventional system. Moreover, the characteristic of EMG signal obtained by Myo-Armband in terms of frequency spectrum properties was closed to the ideal shapes. In performance testing by EMG feature extraction evaluation, they concluded that the Myo-Armband is more robust in class-separability than the conventional EMG system. Moreover, the Myo-Armband is more comfortable than the conventional EMG system since the dry electrode is embedded in the device without the use of medical gel to improve the impedance and half-cell potential, resulting in the stability of the signal as show in the experiment results. In [5] a methodology was proposed by the authors to classify the default actions of the Myo-Armband using machine learning techniques. They evaluated the performance of MLP, KNN, LDA, QDA, Decision Tree (DT), and Naive Bayes (NB) classifier. They have reported achieving overall high accuracy of greater than 90% on single movements with MLP. LDA, KNN, QDA, and DT have shown the accuracy of around 80%. NB was shown to have poor accuracy. They have suggested expanding the feature vector to improve accuracy. The features considered in this study are Mean of the Absolute Value of the signal (MAV), Integrated EMG

(IEMG), Root Mean Square value of the signal (RMS), and Variance of Signal (VAR). In [6], a gesture recognition using SEMG in the transient state is proposed. The classification algorithm used was SVM with Gaussian Kernel (SVM-G) and Discrete Wavelet Transform (DWT). The study considered the 5 default gestures of the Myo-Armband. A window size of 750ms was used and an accuracy of 87.5% was achieved in this study. In [7] an SVM classification model that classified gestures from SEMG data with an accuracy of 89% was proposed. They have suggested pre-processing the original data to eliminate the effect of noise by using absolute value function and a Butterworth low-pass filter. In [8] a sensor fusion. technique was proposed using the SEMG data from the SEMG sensors and Inertial Measurement Unit data of the Myo-Armband to classify user-independent hand gestures using MLP. The classifier model was reported to perform with an average accuracy of 78.94%. They have demonstrated that it was possible to have a more intuitive human-machine interface that allowed better control of wearable machines. The gestures classified were the default gestures of the Myo-Armband. In [9] a real-time hand gesture classification system using artificial Neural Network (ANN) was proposed. They have reported an accuracy of 96%. The features considered were time-domain features. The gestures used were the default armband gestures and an accuracy of 85.08%±15.21% was reported. They have reported a slight delay between the onset of the gesture and the recognition of the gesture attributing it to the use of the sliding window technique. Based on the reviewed literature the classification algorithms suggested by most of the authors were SVM, ANN, DT and LDA. Therefore, these were the primary algorithms considered along with Logistic Regression (LR), Random Forest (RF), KNN and Gaussian Naïve Bayes (GNB). PCA and LDA were the two dimensionality reduction techniques used in addition to use of CNN. Papers [10-18] all shed light on the different Time Domain and Frequency Domain features that can be extracted from the Electromyography signal. In [19] a CNN based feature extraction methodology was proposed. Authors have proposed a CNN that could perform feature extraction effectively. They have reported an improvement in accuracy by 4.35%, 3.62% and, 4.7% for Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and K Nearest Neighbours (KNN) with a combination of CNN extracted features and traditional features. They also proposed the use of CNN for dimensionality reduction. In [20] and [21] the authors have a proposed a fast, adaptive user specific 1-D CNN for classifying ECG signal. They demonstrated an accuracy of greater than 95% for classifying ECG data. They have suggested that 1-D CNN model could be used for fast personalized compact devices for classifying patient specific ECG data. In [22] and [23],

the authors have proposed a 1-D CNN model for detection of structural damage from vibrational data. The data used was the measured acceleration values which was in the range of 5-50Hz random excitations. The acceleration measurements were sampled at 200Hz using an accelerometer. The model processed this raw acceleration data and computes a single score representing the damage state. In [24] the authors have proposed a 1-D CNN based approach for detection of bearing faults. Raw vibrational data from the bearings. An accuracy of 97% was recorded during the fault detection. In [25] the authors have suggested a 1-D CNN based approach for fault detection in bearings. They were able to demonstrate that 1D CNNs are capable of providing efficient training of the model with limited data and limited number of backpropagation iterations. The model was able to perform fault detection with an accuracy of 93%. In [26], the authors have used a 1-D CNN model for real time motor fault detection and monitoring the motor condition. The data used in this study was electric current. The model could detect faults with an accuracy of around 97%. In [27], the authors have made use of a 1-D CNN model for the purpose of detecting switch faults in modular multilevel converter. The authors have also made use of overlapping windows in this study. 10-fold cross validation is done in the study to validate the results. The authors were able to demonstrate an accuracy of 99% for their model.

The papers reviewed during this work included studies done on gesture classification systems using the Myo-Arm Band using machine learning. Some of the literatures suggested the use of 1-D CNN model for pattern recognition in signals such as vibration, electrical current and ECG signals. At the time of the literature survey, no paper was found where 1-D CNN had been used for pattern recognition problems on EMG data. This is the specific area of the research the study focuses on.

2.1 Challenges

The following are the challenges faced during the prediction of classes of data from stochastic biomedical signals such as EMG, ECG or EEG.

a. Biomedical signals such as EMG, EEG and ECG are stochastic in nature. They have a random probability distribution that mat be analysed statistically, but may not be predicted precisely.
b. The information and quality of the data varies with location of the body from where the signal is tapped from.
c. The information and quality of the data varies from person to person for the same gesture.
d. The information contained in the biomedical signal will vary from person to person based on their muscles, health condition, age etc.
e. The data acquisition process can be tedious and time consuming and prone to fatigue as the participants have to flex and relax their muscles a number of times repeatedly.

2.2 Opportunities

From the literature it was found that there is ample scope for research work. The following are the opportunities identified.

a. The biomedical signal being stochastic in nature, is not very easy to process using conventional amplitude detection systems. However, machine learning and deep learning algorithms are useful for identifying patterns in such stochastic data and they can gain insights that the human eye may miss.
b. The Myo-Arm band sensor is not a clinical instrument, but is a commercially available off-the-shelf wearable device that can be easily worn and data can be acquired in a non-invasive manner. The non-invasive nature of the data acquisition device takes away the apprehension or fear the participants may have with needle electrodes associated with intramuscular electrodes.
c. With the availability of commercial high performance computing devices, training and evaluation of learning algorithms is well within the grasp of researchers

3. Problem Statement

In a prosthetic device, that requires a Human Machine Interface (HMI), a gesture recognition system that is programmed or hard coded to identify hand gestures, is not an efficient method of classifying hand gestures. Machine learning and Deep Learning methodologies can be applied so that the machine can be made to learn about the user's hand gesture data set and it can classify the intended gestures based on the knowledge it has gained. Explicit instruction need not be given to the machine about the identity of the hand gesture, the machine will learn that by itself. The advancements in computing systems and significant improvements in tools for developing machine learning software has given a lot of scope for research and development in the area of machine learning.

The research aims to provide an intuitive and seamless solution for the gesture recognition problem for a human machine interface that takes as input surface EMG signals which is acquired by non-invasive methods powered by Artificial Intelligence.

4. Objectives

The proposed research objectives were focused on developing a learning model to classify hand gestures which can be used in gesture recognition systems The following goals were determined to be worked on:

1. Recognition of different hand gestures based on the acquired data sets using different features and classification algorithms.
2. Determination of the best suited features and classification algorithm for classifying EMG data.
3. Compare the performance metrics for different Machine Learning Algorithms with the performance of a 1-D Convolutional Neural Network Deep Learning Model for hand gesture recognition system on a suitable commercially available computing system.

5. Methodology to Recognize Hand Gestures

While conducting research, a systematic methodology is followed to investigate a phenomenon. A systematic process is followed for collecting the data in a controlled environment and then the data is organized, synthesized, analysed and interpreted to gain insights about the phenomenon under investigation. In this study data is acquired from multiple users of different age group, gender and profession to avoid any type of bias. The data is then stored locally on a Hard Disk Drive and backed up in cloud. Different algorithms can now be applied on the acquired data and the performance of the algorithm can be evaluated.

In this study, the aim was to recognize five different hand gestures including Rest. The gestures performed in this study are shown in the Fig. 1. The gestures are Point, Middle Finger Extension, Grip, Pinch and Rest. A Myo-Armband was worn by the user on the forearm. The Myo-Armband consist of 8 data acquisition units which will acquire tap into the Surface EMG signal. The Myo-Armband is paired with a computing device that acts as a data acquisition system via Bluetooth. A software was developed using Python programming language to interface with the Myo-Armband and to automate the tasks involved in the process of data acquisition. The software was designed so that a uniform time period could be maintained between each gesture contraction and rest. The software prompted the user to perform a gesture and to relax. The software also made it convenient to name the file and store the file by automating the process of collecting the users name, type of gesture and session number at the beginning of every session. The study was conducted in two parts. The first part of the research work was to evaluate the performance of machine learning models in classifying hand gestures. The second part of the study was to evaluate the performance of a deep learning model in comparison with the machine learning models.

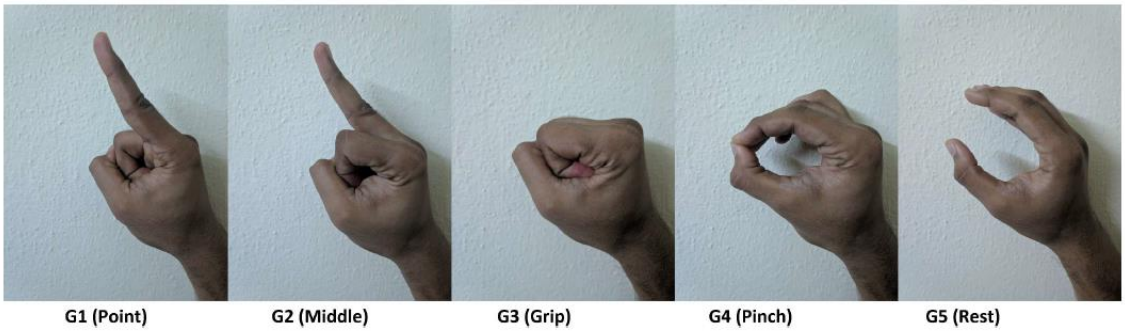

Fig 1. Hand Gestures used in the study

As EMG signals are stochastic in nature, amplitude alone is not sufficient to recognize distinct patterns in the SEMG signal. Feature extraction has to be performed on the data. Segmentation is first done on the data using disjoint window technique. Then time-domain features are extracted from each processing window. In the case of the deep learning model the deep learning network consists of two parts, the Feature Extractor and the Classifier. The features are extracted by the sequence of 1 dimensional convolution and pooling layers of the deep learning model. The acquired data is then split into training data set and validation data set and a suitable algorithm is applied to recognize gestures. The models are trained with the training data and the performance is evaluated using the validation data. The plan is to apply machine learning algorithms and apply deep learning concepts at a later stage for analysis. The learning models are then evaluated based on the performance metrics. The training phase is shown in Fig. 2 and the Testing Phase is shown in Fig. 3.

The experiment was done in 3 parts. The first part of the study was to evaluate the performance of models built using machine learning algorithms Logistic Regression, Decision Tree Classifier, Random Forest Classifier, Support Vector Machine with Linear Kernel and Radial Basis Function Kernel, K-Nearest Neighbours Classifier, Naïve Bayes Classifier and Artificial Neural Network.

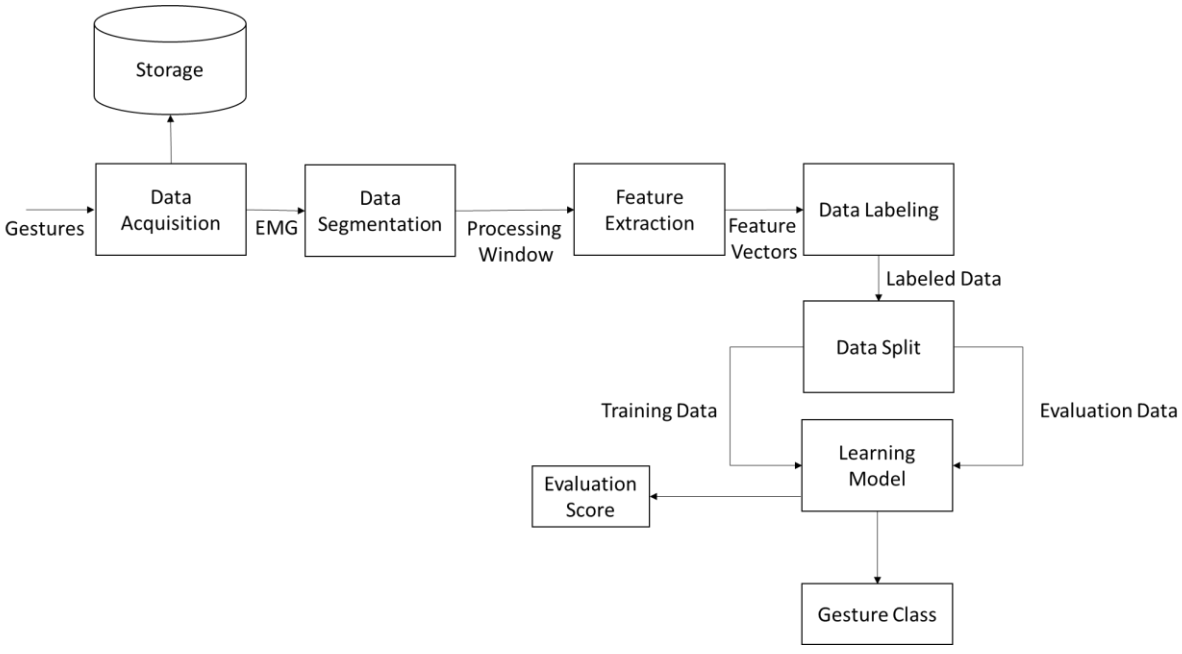

Fig 2. Training and Validation Phase

In the second part of the study, the effects of applying dimensionality reduction on the time-domain features was evaluated. In the third part of the study a deep learning model i.e. a One Dimensional Convolutional Neural Network was trained and its performance was evaluated.

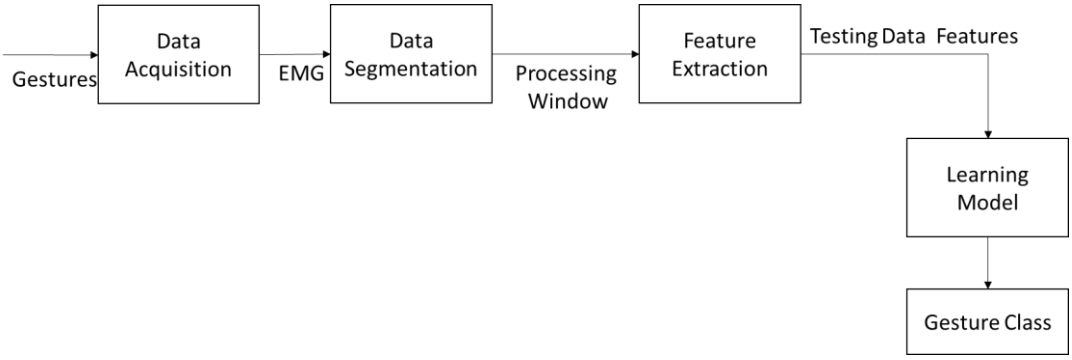

Fig 3. Testing Phase

6. Hardware and Software System for Gesture Classification

The experimental setup consists of a Myo-Armband and a computer equipped with a custom developed software for performing data acquisition, model training, evaluation and testing. The user wears the Armband on the forearm. The user has to wear the armband at the same location if the data was acquired over different sessions. This is because the EMG data fluctuates with the sensor displacement.

6.1 Hardware for Data Acquisition

The Surface EMG Signal is recorded using the Thalmic Labs Myo-Armband. The armband and its Bluetooth dongle are shown in Fig. 4. which is a commercially available EMG acquisition Device. This device has 8 Surface EMG sensors. The Myo-Armband can be interfaced with a computer via a Bluetooth Dongle. The Myo-Armband has a sampling frequency of 200Hz implying that it reads one sample in every 5ms from each of the 8 sensors. The laptop chosen for this application consisted was equipped with an NVIDIA RTX2060 GPU and 32GB of RAM and an AMD Ryzen 7 Processor. The specification was sufficient for training machine learning and deep learning models. The specific computing system with NVIDIA GPU was chosen as the deep learning model is built using the Tensorflow platform and Tensorflow in GPU mode only supports NVIDIA GPU as of today.

Fig 4. Thalmic Labs Myo-Armband and Bluetooth Dongle

6.2 Software for Data Acquisition

The software used for the purpose of automating data acquisition was developed using Python programming language. The software requests the user to enter the name of the user, type of gesture and session number. These parameters are then used when generating the final file with data. The Software prompts the user to perform a gesture or relax. The duration for each gesture action is 5 seconds and for relax is 3 seconds. The software ensures that each gesture is therefore available within their respective windows. When the user is prompted to flex, the user performs the gesture and when prompted to relax the user relaxes. The EMG signal is recorded and the sampled values are stored in a CSV file every 5ms. This is the raw data set that we will be processing further. Fig. 5. Shows the interface provided to the user for entering the information and the prompt shown to the user for flex and relax.

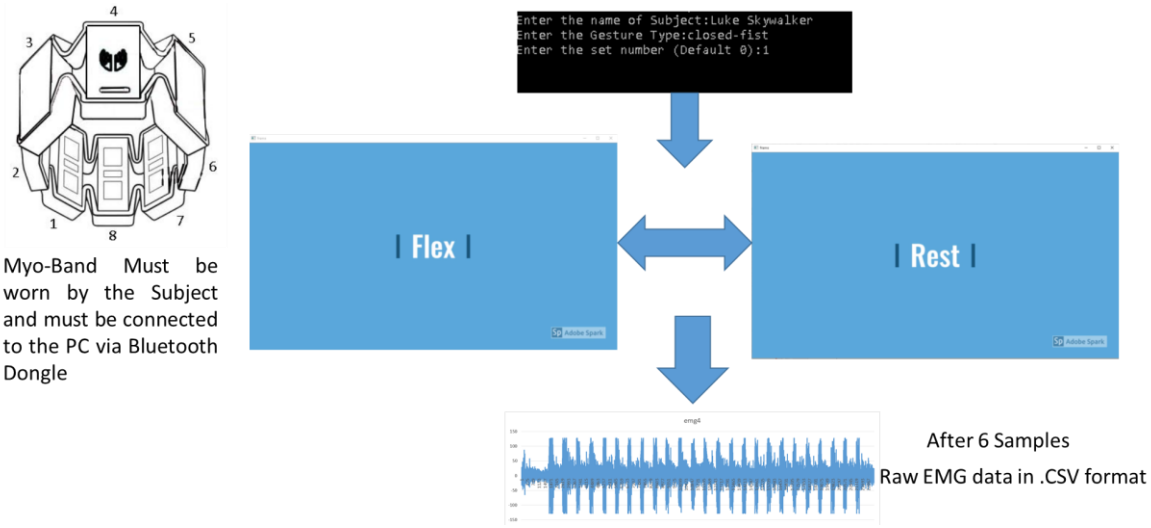

Fig 5. Software Interface for Data Acquisition

7. Data for Gesture Classification

Data was collected from 10 users of different age groups in the range of 18-35 years who work in different professions. Out of the 10 users, the study was conducted on randomly chosen 5 users. The number of samples collected for each participant for the five gestures is 72 each. When the user is prompted on the screen the user performs the gesture and holds it for 5s and then relaxes for 3 seconds. This cycle is repeated 6 times in a session. The number of cycles were set to 6 to avoid the effect of muscle fatigue. 12 such sessions are recorded for every participant giving a total of 72 samples for each gesture and 360 sample for each user. A sample of a window of EMG signal is shown in the Fig. 6. The raw data extracted from the 8 sensors is stored in a CSV file as shown in the Fig. 7.

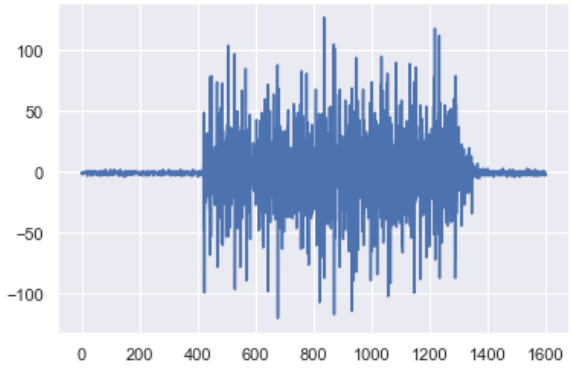

Fig 6. A Window of Surface EMG Data

The data is then studied to identify the onset of the gesture to identify the processing window trigger points. The trigger points are noted. Each processing windows will be of 8s duration. The trigger points are used to indicate the beginning of an 8s window. Data from one sensor is sufficient for this application. Therefore, data from one sensor is taken. Each Gesture Window is then arranged in a CSV file row wise, where each row represents 1 window. Each row of dataset is then labelled with 0,1,2,3 and 4 corresponding to gestures G1, G2, G3, G4 and G5. As shown in the Fig. 8. The data was segmented using Disjoint window technique.

For the evaluation of the deep learning model, K-Fold cross validation with K=5 was performed. The K-Fold Cross Validation performed was stratified, so that the data was split into folds ensuring that each fold had same proportion of samples with the given labels. The entire data set is split into 5 stratified folds. This will enable us to validate the performance of

the model with 5 different folds of data and obtain Mean Accuracy of the proposed model. The process of K-Fold Cross validation is as shown in Fig. 9.

	slno	emg1	emg2	emg3	emg4	emg5	emg6	emg7	emg8	Time
0	0	3	2	4	5	5	5	6	3	0.000
1	1	5	7	10	9	8	9	8	7	0.005
2	2	-5	-7	-8	-7	-8	-8	-7	-7	0.010
3	3	-5	-6	-5	-6	-6	-6	-5	-4	0.015
4	4	2	2	0	2	3	2	1	0	0.020
...	...	...	...	...	...	...	...	...	...	...
12196	12196	0	0	0	1	-1	-1	0	-1	60.980
12197	12197	-2	-1	-2	-3	-2	0	-2	-1	60.985
12198	12198	-2	-1	-4	-2	-1	-3	-3	-2	60.990
12199	12199	0	0	0	0	-1	1	0	0	60.995
12200	12200	0	0	0	0	0	-1	-2	-1	61.000

12201 rows × 10 columns

Fig 7. Raw EMG Data

	0	1	2	3	4	5	6	7	8	9	...	1591	1592	1593	1594	1595	1596	1597	1598	1599	label
0	0	-1	-1	0	0	-3	-1	0	0	0	...	0	2	-1	0	0	-1	-1	-2	-2	0
1	-1	0	0	0	0	2	-1	-2	0	-1	...	-1	-2	-2	-1	0	-2	-2	0	-1	4
2	1	-1	-1	0	-1	0	-2	0	-1	0	...	-1	-2	-2	2	0	0	-1	-1	-3	1
3	0	-1	-1	-1	0	-2	-2	0	-1	1	...	1	-1	0	-1	-1	0	-2	-2	-1	1
4	0	-1	0	0	-1	-1	-1	-2	-1	-2	...	2	0	-1	-1	1	0	4	1	-2	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
355	-1	-1	-1	0	-1	-1	0	0	0	-1	...	-2	1	-2	-3	-1	-1	-2	1	0	0
356	2	-4	1	-1	1	-3	-1	-2	-5	1	...	-1	1	0	-5	0	0	-3	-3	-2	4
357	-2	1	-2	0	0	-1	-2	-1	-1	-1	...	-1	-1	-2	-2	1	1	-3	0	1	2
358	-3	4	-27	14	-5	9	-35	9	5	1	...	1	-1	-1	-2	0	-1	1	-1	1	1
359	0	0	0	-3	1	-2	0	-1	-1	1	...	0	-1	-3	0	-1	-1	-1	-2	0	0

360 rows × 1601 columns

Fig 8. EMG Data - Processing Windows arranged Row-Wise

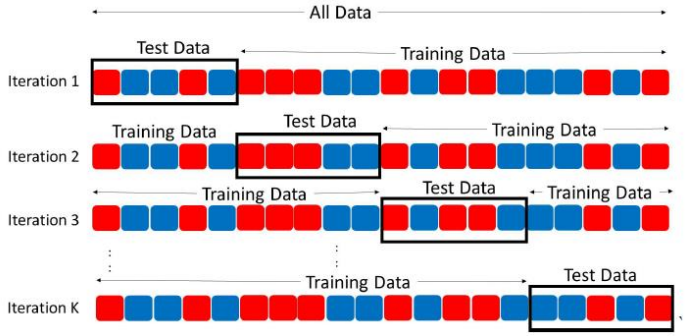

Fig 9. K-Fold Cross Validation

8. Feature Extraction, Dimensionality Reduction and Classification

The Surface EMG Signal is stochastic in nature and has a random probability distribution. It has a pattern that may be analysed statistically but may not be predicted precisely. In order to get some insights from the Raw Surface EMG Data, Features have to be extracted from each processing window of data. The features considered are of two types. For evaluation of machine learning models, Time-Domain Features were identified and extracted. The time domain features considered are Integrated EMG (IEMG), Mean Absolute Value (MAV, MAV1 and MAV2), Simple Squared Integral (SSI), Variance (VAR), Root Mean Square (RMS), Waveform Length (WL), Average Amplitude Change (AAC), Absolute Standard Deviation Value Difference (DASDV), Myo-Pulse Percentage (MYOP), Log Detector (LOG), Willison Amplitude (WAmp), Slope Sign Change (SSC) and Number of Zero Crossings (ZC) and Amplitude of First Burst (AFB). The extracted features are arranged row-wise, where each row represents the feature vector corresponding to a processing window as shown in the Fig. 10. Each column in a row represents a time-domain feature.

	MAV	MAV1	MAV2	SSI	VAR	TM3	TM4	TM5	LOG	RMS	WL	AAC	AFB	MYOP	WAMP	SSC	label
0	6.028554	5.396637	5.459205	151598.212090	94.808138	21.546922	55182.657446	1.793598e+04	415.114166	9.733904	11795.364276	7.372103	0.004272	0.991250	800.0	400.0	1
1	0.445955	0.334276	0.220175	503.528588	0.314902	0.033620	0.298232	1.141219e-01	1.561982	0.560986	804.475959	0.502797	0.064823	0.988125	786.0	338.0	4
2	8.227068	6.932964	7.130886	295751.717103	184.960423	381.660100	248257.186842	2.410998e+06	3740.849845	13.595765	15796.333014	9.872708	0.199162	0.990625	809.0	378.0	1
3	0.500328	0.372946	0.245549	618.078692	0.386541	0.022242	0.423909	5.283207e-02	1.649263	0.621530	965.817473	0.603636	0.057677	0.986250	782.0	361.0	4
4	8.263915	7.492572	7.681053	276144.372415	172.698169	176.426267	146375.826130	3.782570e+05	3881.258550	13.137360	16819.742652	10.512339	0.073259	0.991875	799.0	371.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
355	2.398098	2.011376	1.640112	21755.252718	13.605536	0.990490	1306.182240	1.680775e+03	11.002227	3.687415	4630.845457	2.894278	-0.004426	0.991875	797.0	355.0	3
356	7.435123	6.576412	4.970865	197521.726630	123.528284	241.211676	71819.413594	4.687191e+05	1694.465495	11.110854	14610.752445	9.131720	-0.060640	0.996250	805.0	361.0	0
357	1.921145	1.590413	1.418279	14499.526496	9.067871	5.835849	1042.509381	3.102490e+03	6.828775	3.010349	3793.239860	2.370775	0.021521	0.990625	791.0	375.0	3
358	7.588581	6.177541	6.070952	228697.903425	143.025581	127.635102	116893.923662	6.396450e+04	1975.508919	11.955592	14834.850201	9.271781	0.064906	0.995625	810.0	369.0	1
359	7.860272	7.032290	7.098173	242957.652737	151.943498	390.612673	123654.038914	8.409238e+05	2592.224704	12.322684	15168.346590	9.480217	-0.124009	0.993750	801.0	341.0	1

360 rows × 17 columns

Fig 10. Time Domain Features for each processing window arranged Row-Wise

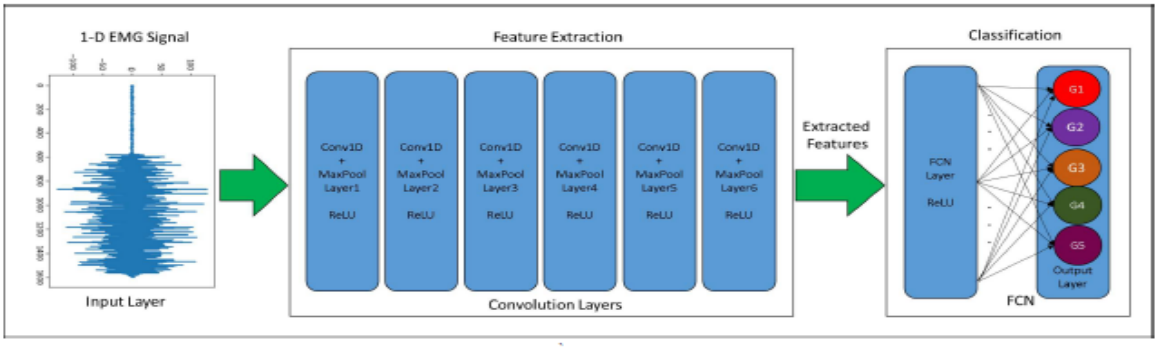

Fig 11. 1-D Convolution Neural Network Model

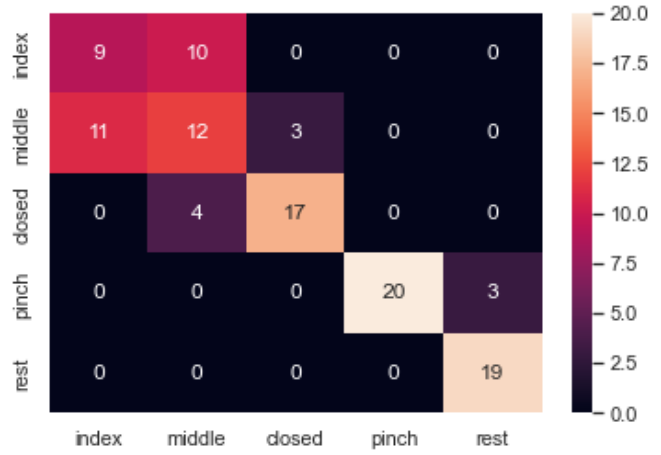

Fig 12. Confusion Matrix for Logistic Regression

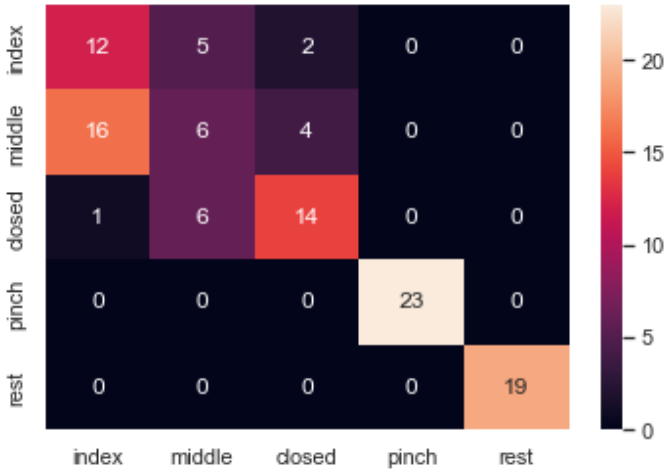

Fig 13. Confusion Matrix for Decision Tree

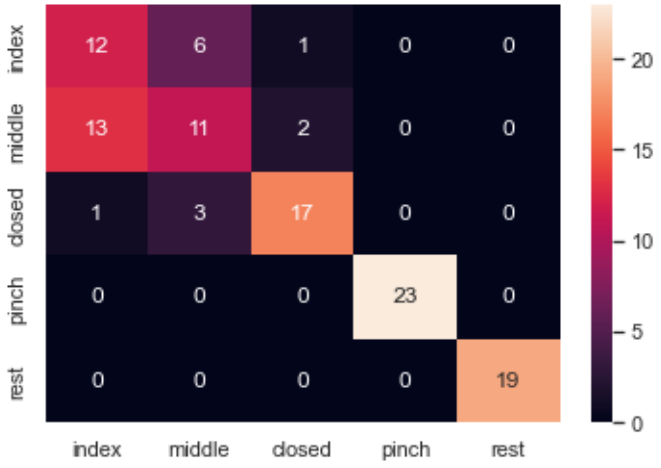

Fig 14. Confusion Matrix for Random Forest

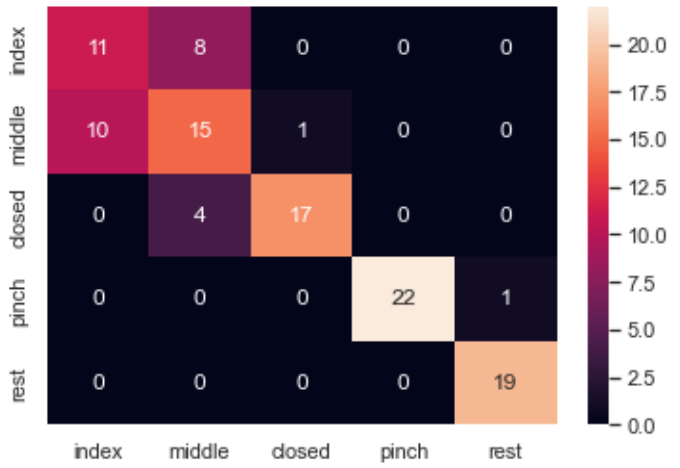

Fig 15. Confusion Matrix for SVM (Linear Kernel)

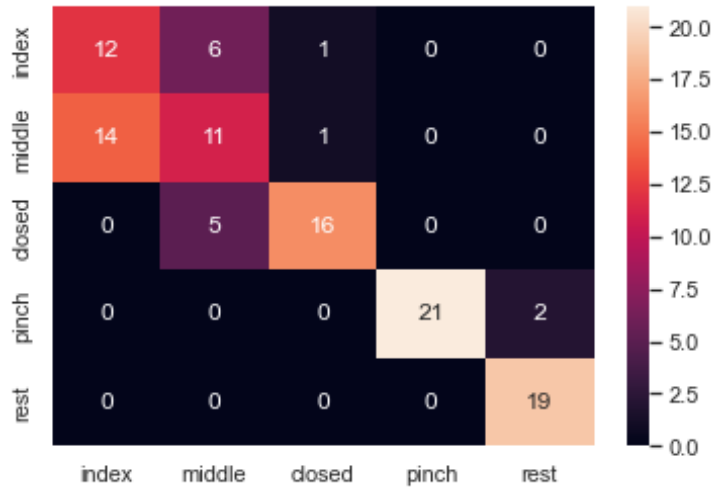

Fig 16. Confusion Matrix for SVM (RBF Kernel)

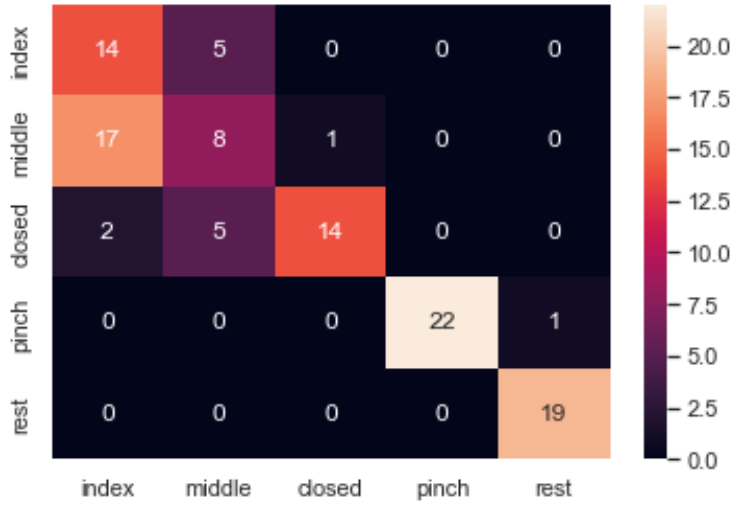

Fig 17. Confusion Matrix for K-Nearest Neighbours

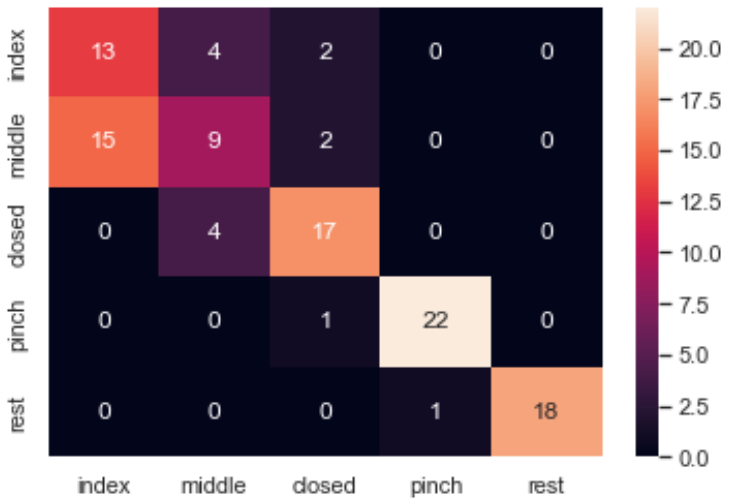

Fig 18. Confusion Matrix for Gaussian Naïve Bayes

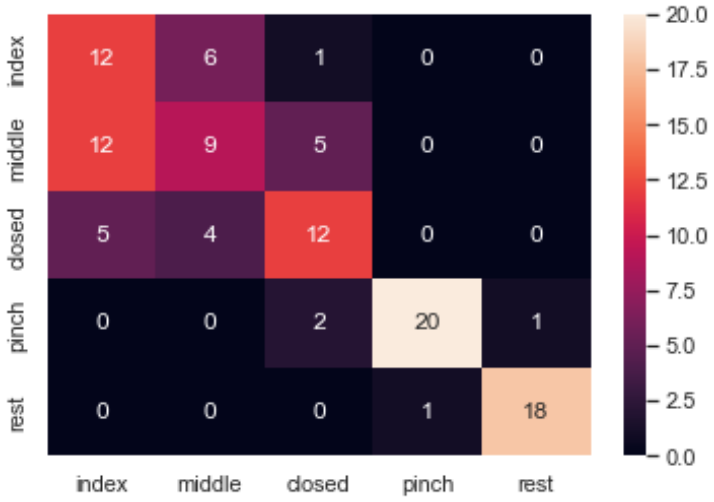

Fig 19. Confusion Matrix for Multilayer Perceptron

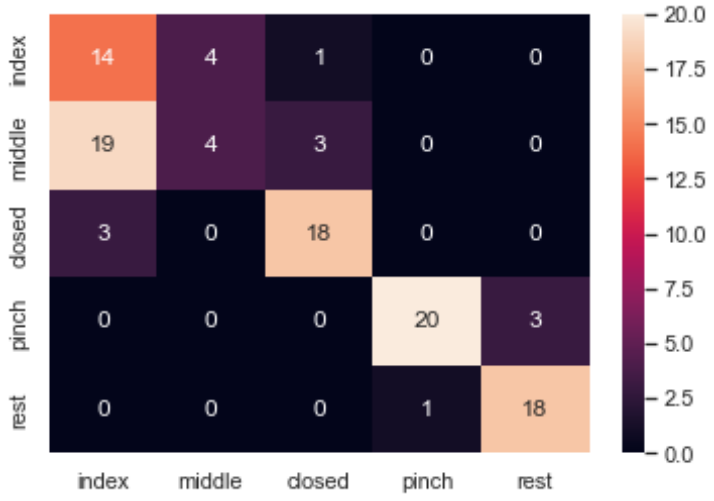

Fig 20. Confusion Matrix for Logistic Regression with PCA

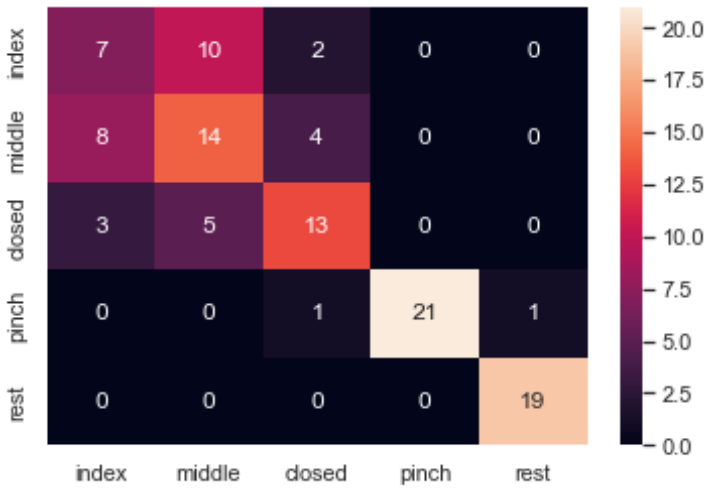

Fig 21. Confusion Matrix for Decision Tree with PCA

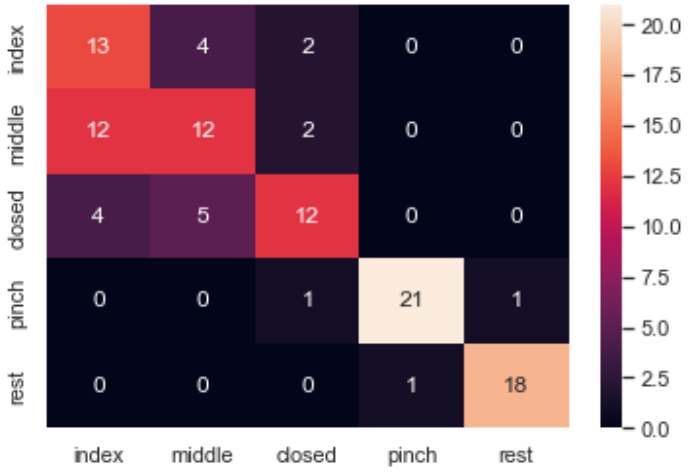

Fig 22. Confusion Matrix for Random Forest with PCA

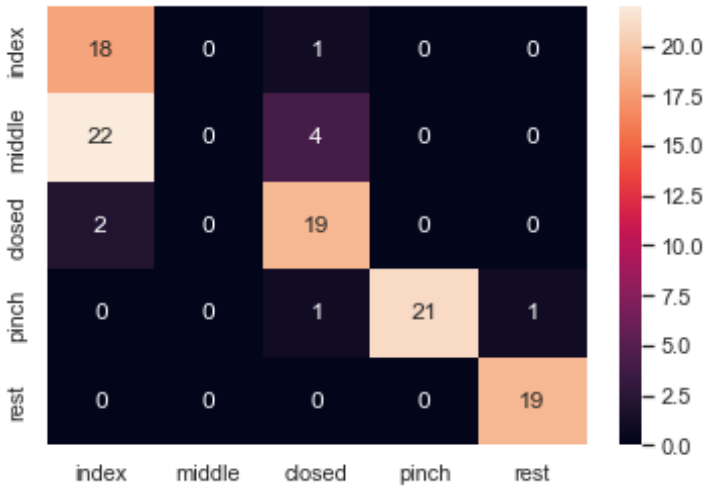

Fig 23. Confusion Matrix for SVM (Linear Kernel) with PCA

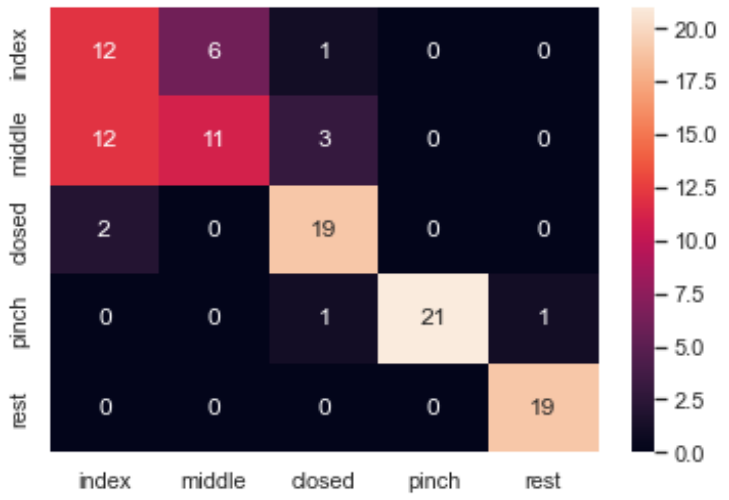

Fig 24. Confusion Matrix for SVM (RBF Kernel) with PCA

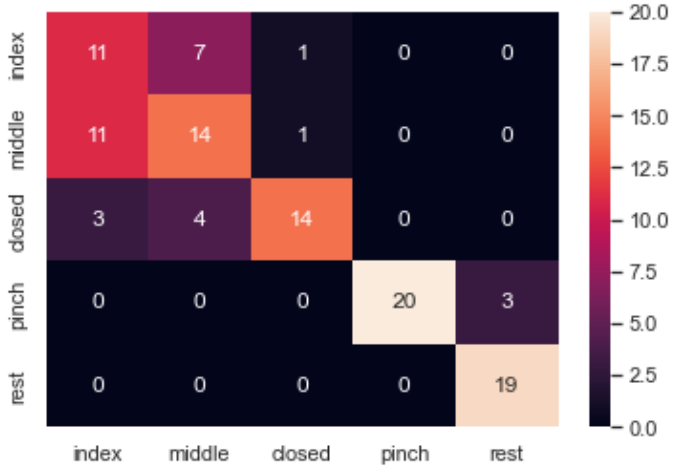

Fig 25. Confusion Matrix for K-Nearest Neighbours with PCA

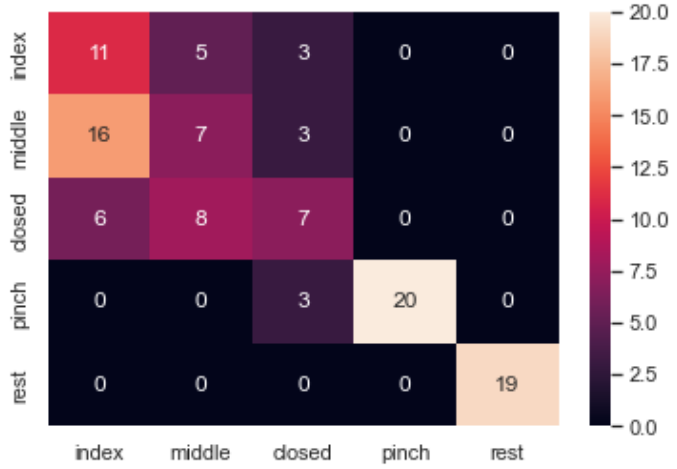

Fig 26. Confusion Matrix for Gaussian Naïve Bayes with PCA

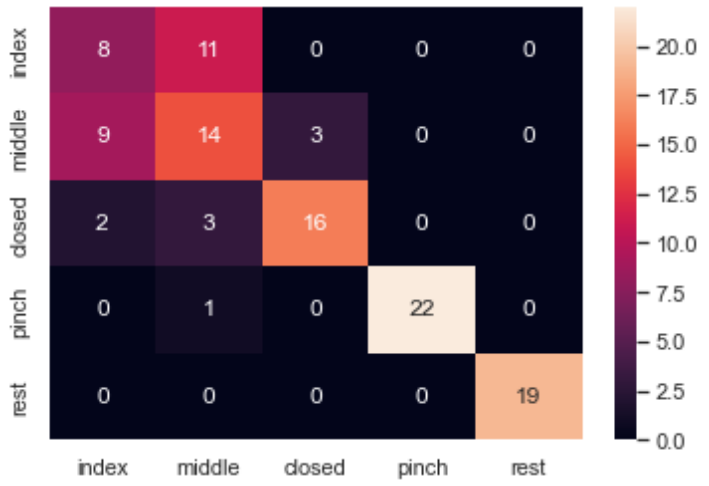

Fig 27. Confusion Matrix for Multilayer Perceptron with PCA

Increasing the number of features does not necessarily imply an improvement in accuracy. Accuracy can improve up to a limit after which it starts declining with the increase in number of features. This is called as Curse of Dimensionality. Decreasing the dimensions by transforming the features is a method of overcoming curse of dimensionality as well as reducing computing load and speeding up the training process. Dimensionality Reduction was applied and the ten time-domain features were transformed into features using Principal Component Analysis. No drop in accuracy was observed which enforced the fact that instead of training the model with all ten features, we could transform the features to a reduced dimension and then the transformed features could be used to train the model without losing accuracy. In the case of one-dimensional convolutional neural network based-deep learning model, feature extraction and dimensionality reduction are done by the series of convolution and pooling layers as shown in Fig. 11. The details of the CNN Model are described in TABLE I. To implement the gesture classification system, the EMG data was used to train multiple machine learning models such as logistic regression, decision tree classifier, random forest classifier, naïve bayes classifier, support vector machine with linear and radial basis function kernels.

Performance metrics used to evaluate model performance can be computed using the Confusion Matrix. The performance metrics used for evaluating the model are Accuracy (ACC), Precision (PR), Recall (RE) and F1-Score (F1). The number of samples that are correctly classified as Positive are called True Positives (TP). The number of samples that are incorrectly classified as Positive are called as False Positives (FP). The number of samples that

are correctly classified as Negative are called True Negatives (TN). The number of samples that are incorrectly classified as Negative are called as False Negatives (FN). Confusion Matrix was calculated for each of the learning methods to evaluate performance.

$$Accuracy\ (ACC) = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision\ (PR) = \frac{TP}{TP+FP} \quad (2)$$

$$Recall\ (RE) = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score\ (F1) = 2 \times \frac{PR\ .\ RE}{PR+RE} \quad (4)$$

TABLE I - 1-D CNN MODEL SUMMARY

L.No.	Layer	Output Shape	Parameter
1	Conv 1D	(None,1599,16)	48
	Maxpooling	(None,799,16)	0
2	Conv 1D	(None,798,64)	1088
	Maxpooling	(None,399,64)	0
3	Conv 1D	(None,398,32)	2080
	Maxpooling	(None,199,32)	0
4	Conv 1D	(None,198,16)	528
	Maxpooling	(None,99,16)	0
	Dropout	(None,99,16)	0
5	Conv 1D	(None,98,8)	136
	Maxpooling	(None,49,8)	0
	Dropout	(None,49,8)	0
6	Conv 1D	(None,48,4)	36
	Maxpooling	(None,24,4)	0
	Dropout	(None,24,4)	0
7	Flatten	(None,96)	0
	Dense	(None,50)	5050
8	Dense	(None,5)	255
Total Trainable Parameters		12765	

The accuracy and other performance metrics of the classifier models without using dimensionality reduction is as shown in TABLE II. The accuracy of the classifier models with PCA dimensionality reduction applied is as shown in TABLE III. The confusion matrix for the Machine Learning Models without PCA Dimensionality Reduction is shown in, Fig. 12., Fig. 13., Fig. 14., Fig. 15., Fig. 16., Fig. 17., Fig. 18 and Fig. 19. The confusion matrix for the Machine Learning Models with Dimensionality reduction is shown in Fig. 20., Fig. 21., Fig. 22., Fig. 23., Fig. 24., Fig. 25., Fig. 26. and Fig. 27., The accuracy and Loss curves for the 1-D CNN Deep Learning model is shown in Fig. 28. And Fig. 29. Respectively. The average accuracy for the 5 users is as shown in the TABLE IV.

TABLE II - PERFORMANCE METRICS FOR THE MODELS WITHOUT PCA

Metric	**LR**	**DT**	**RF**	**SVM(L)**	**SVM(R)**	**KNN**	**NB**	**MLP**
ACC	71	69	76	78	73	71	73	66
PR	72	68	77	79	75	74	74	67
RE	71	69	76	78	73	71	73	66
F1	72	68	76	78	73	71	73	66

In TABLE II it can be observed that SVM with linear kernel performed with the best accuracy and Multi-Layer Perceptron performed with the least accuracy. It can be observed that the accuracy for all the models is in the range of 66%-78%. In TABLE III, it can be observed that there is a drop in accuracy for LR, RF, SVM with linear Kernel and NB. An increase in accuracy is observed in SVM with RBF kernel and MLP. A significant increase is observed in the accuracy of MLP and a significant decrease in accuracy is observed with the NB model. In TABLE IV it can be observed that the accuracy for 5 users is consistently in the range of 79% to 82% with a deviation of ±2% to ±4%.

The results observed during the course of this research work are presented in [28] and [29], where surface electromyography data acquired from a commercial SEMG acquisition device is considered [31]. The research work presented in [28] describe the performance of classical machine learning techniques applied for the classification of SEMG signals and [29] explores the effects of dimensionality reduction on classification accuracy. The conclusion was that dimensionality reduction does not cause any significant drop in accuracy. The research work presented in [30] explores the results obtained by classifying Hand Gestures from surface

EMG using a deep learning model and the data from [32]. An extension of dataset [32] is [33] which contains the spectrogram of the EMG Data.

TABLE III - PERFORMANCE METRICS FOR THE MODELS WITH PCA

Metric	**LR**	**DT**	**RF**	**SVM(L)**	**SVM(R)**	**KNN**	**NB**	**MLP**
ACC	69	69	70	71	76	72	59	73
PR	70	69	72	60	77	75	62	74
RE	69	69	70	71	76	72	59	73
F1	66	69	71	64	76	73	60	74

TABLE IV - 1-D CNN OBSERVED ACCURACY FOR 5 USERS

Iteration	**Accuracy User 1**	**Accuracy User 2**	**Accuracy User 3**	**Accuracy User 4**	**Accuracy User 5**
1	82%	80%	78%	82%	81%
2	78%	82%	79%	79%	78%
3	88%	78%	78%	78%	78%
4	82%	82%	81%	82%	81%
5	79%	78%	80%	79%	77%
Average Accuracy	82%±3%	80%±3%	79±4%	80%±3%	79%±2%

From the results it is evident that the 1-D CNN deep learning model proposed in this study consistently performs better than the classical machine learning models.

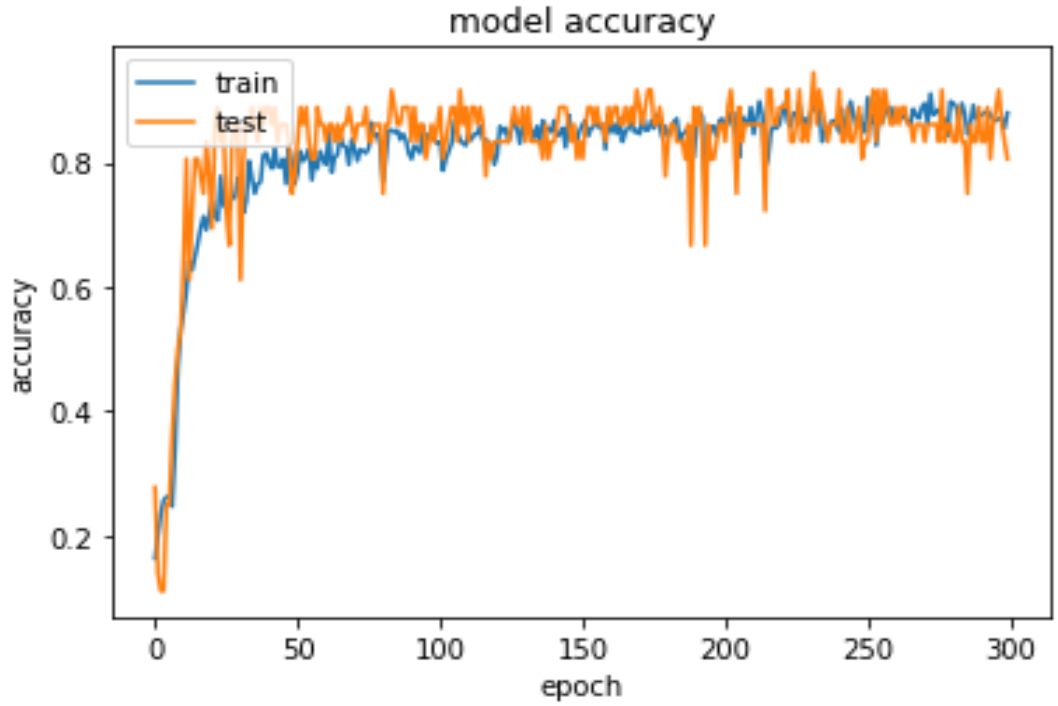

Fig 28. Accuracy Curve for the Proposed 1-D CNN Model

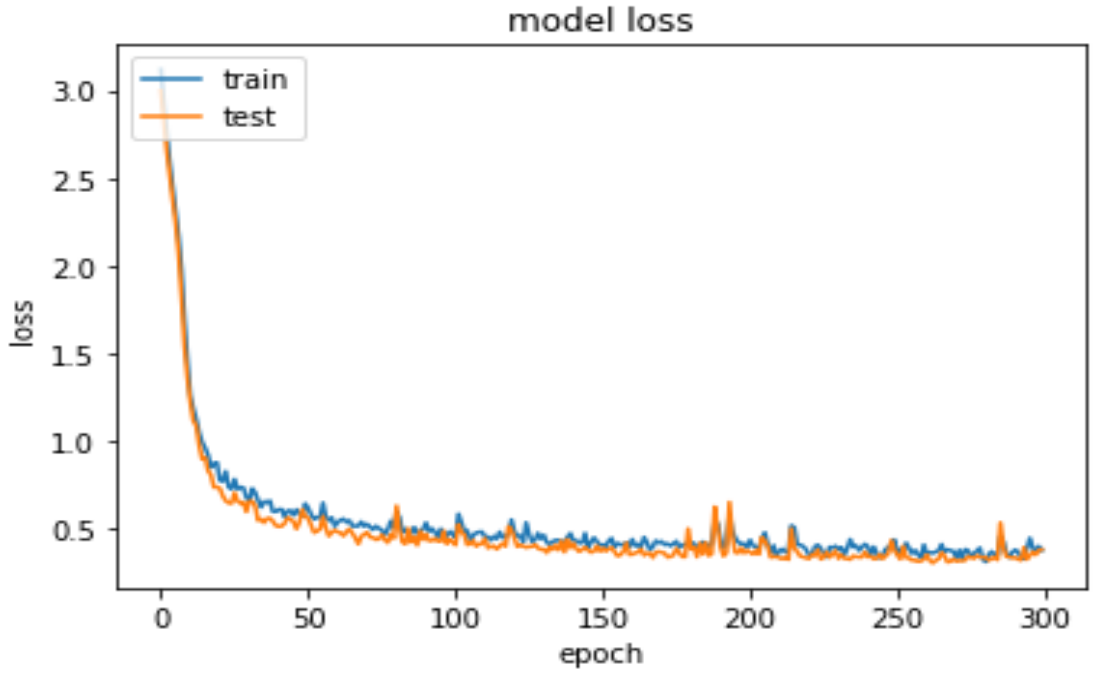

Fig 29. Loss for the Proposed 1-D CNN Model

9. Conclusion and Future Scope

9.1 Conclusion

It can be observed from the results that both machine learning and deep learning models can be used for classifying hand gestures from surface EMG Signal acquired from commercially available off-the-shelf devices such as the Myo-Arm Band. It was also possible to train the deep learning model and the machine learning model on a commercially available computing system. Further it was observed that the 1-D CNN based deep learning model proposed in this study consistently performs better than the classical machine learning models with an average accuracy in the range of 79-82%. Disjoint window segmentation was used in this study. This work can be extended in future to use overlapping window segmentation technique.

9.2 Future Scope of Work

The scope of the study was limited to implementing a suitable learning model that can be used to classify hand gestures from surface EMG data acquired from commercially available devices. The1-D CNN model shows promising results and it can be implemented on suitable miniaturized computing systems as they become available in the market and use the hardware to control prosthetic limbs, exoskeletons, sign-language to audio generators and other machinery.

This methodology can be further extended for classification of unique patterns in EEG signals acquired from Brain Computer Interfaces (BCI). Use of EMG restricts the application of this method for a multi-function prostheses arm. The functions of the prosthesis would be limited to the number of unique muscle contractions possible with the residual limb of amputees. However, with the use of BCI this limitation can be overcome.

Prosthetic Limbs with real-time classification of EMG signals using online-classification can be developed. Overlapping window segmentation would have to be used for this application instead of disjoint window segmentation to reduce the delay between the onset of the gesture and the actuation of the motors of the prosthetic limbs.

9.3 Thesis Outline

Chapter 1: Introduction

This chapter briefly describes Electromyography and Machine Learning and Deep Learning concepts with their challenges and introduces the work and the necessity of carrying out this work.

Chapter 2: Gesture Recognition Systems

This chapter provides information on Myoelectric Systems and its role in Human Machine Interfaces and its challenges

Chapter 3: Literature Survey

Describes the work carried out in this field earlier as well as identifies the challenges and opportunities in implementing myoelectric gesture recognition system. It summarizes the work carried out in the field of Electromyography and EMG based Gesture Recognition Systems

Chapter 4: Hardware and Software System for Data Acquisition

This chapter provides a brief design of hardware and software system used to acquire the EMG Data from the users

Chapter 5: EMG Data for Gesture Recognition

Summarizes the dataset and its attributes in analysis. The chapter provides an in depth description of the data set used in the study and its acquisition process

Chapter 6: Classification of Hand Gestures from Surface EMG Data

This chapter explains the learning algorithms and its metrics in recognizing hand gestures from surface Myoelectric Signal.

Chapter 7: Comparison of algorithm performance for Gesture Recognition.

Summarizes the result of the learning algorithms by comparison to establish the best algorithm.

Chapter 8: Gesture to Speech and Text Translation Application

Summarizes the implementation of a myoelectric control system to translate gestures to speech and text

Chapter 9: Conclusion and Future Scope.

This chapter concludes the thesis with summary and discusses the limitations of the approach taken. Finally, some suggestions are provided which can extend the research that has been accomplished in this study.

9.4 List Of Publications

Data set publication

1. P. Amin and A.M. Khan, "Raw Surface Electromyography Dataset from Myo Arm Band", in Mendeley Data, V1, March, 2021, doi: 10.17632/d4y7fm3g79.1
2. P. Amin and A.M. Khan, "EMG Data Set for Machine Learning and Deep Learning Problems", Mendeley Data, March 2022 V1, doi: 10.17632/3r6hynp5xs.1
3. P. Amin and A.M. Khan "Spectrogram of Surface EMG Data obtained from Myo Armband", Mendeley Data, V2, August, 2022, doi: 10.17632/xz38kw7m3d.2

Publications

1. P. Amin, A.M. Khan, A.R. Bhat and G. Rao, "Feature Extraction and Classification of Gestures from Myo-Electric Data Using a Neural Network Classifier", in: Evolution in Computational Intelligence. Advances in Intelligent Systems and Computing, vol 1176. Springer, Singapore, September 2020
2. P. Amin and A.M. Khan, "A Study on the Effect of Dimensionality Reduction on Classification Accuracy of Myoelectric Control Systems", In: Advances in VLSI, Signal Processing, Power Electronics, IoT, Communication and Embedded Systems. Lecture Notes in Electrical Engineering, vol 752. Springer, Singapore. April 2021
3. P. Amin and A. M. Khan, "A Study on the Application of One Dimension Convolutional Neural Network for Classification of Gestures from Surface Electromyography Data," 2021 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), 2021, pp. 7-11, doi: 10.1109/DISCOVER52564.2021.9663596

Presentations at Conferences

1. Presented a paper titled "*Feature Extraction and Classification of Gestures from Myo-Electric Data Using a Neural Network Classifier*" at the 8th International Conference on Frontiers of Intelligent Computing: Theory and Applications on January 4-5, 2020 at National Institute of Technology- Karnataka, Surathkal, India
2. Presented a paper titled "*A Study on the Effect of Dimensionality Reduction on Classification Accuracy of Myoelectric Control Systems*" at VSPICE-2020 – VLSI, Signal Processing, Power Electronics, IoT, Communication and Embedded Systems as a part of Multi-Conference on International Conference on Emerging Trends in Engineering (ICETE-2020) on December 22-23, 2020 at N.M.A.M.I.T., Nitte, Udupi District, India.
3. Presented a paper titled "*A Study on the Application of One Dimension Convolutional Neural Network for Classification of Gestures from Surface Electromyography Data*" at DISCOVER 2021: International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics on November 19-20, 2021 at N.M.A.M.I.T., Nitte, Udupi District, India.

References

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[3] I. Mendez, B. W. Hansen, C. M. Grabow, E. J. L. Smedegaard, N. B. Skogberg, X. J. Uth, A. Bruhn, B. Geng, E. N. Kamavuako, "Evaluation of the Myo Armband for the Classification of hand motions", 2017 International Conference on Rehabilitation Robotics (ICORR) QEII Centre, London, UK, July 17-20, 2017. pp.1211-1214, 2017

[4] D. Sueaseenak, C. Khawdee, N. Pakornsirikul, C. Sukjamsri, "A Performance of Modern Gesture Control Device with Application in Pattern Classification", 2017, 3rd International Conference on Control, Automation and Robotics, pp.428-431, 2017

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